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Estimation of Annual Average Daily Truck Traffic Volume. Uncertainty treatment and data collection requirements

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Abstract

This paper presents an approach to estimating the Annual Average Daily Traffic (AADT) of trucks along a road section from short period traffic count (SPTC), improving the interpretability of results with the measures of non-specificity and discord. The approach was applied with data obtained in the Province of Venice, Italy, considering the characteristics of SPTCs such as duration and day of the week. The proposed method was found to produce accurate results, particularly for 72-hour SPTCs taken on weekdays. The measures of uncertainty also help to interpret the quality of estimates, and indicate the need for further data collection.

Keywords: Truck AADT Estimate, Artificial Neural Networks, Discord, Non-Specificity

1. Introduction

Collecting data and predicting traffic patterns for planning are the basic responsibilities of transportation agencies. For pavement design, fuel-tax revenue projection and highway planning, information on Annual Average Daily Traffic (AADT) is essential information. Unfortunately, monitoring activities, necessary for accurate AADT estimates, are expensive in terms of costs and personnel.

The Traffic Monitoring Guide (TMG) [1], issued by the US Federal Highway Administration, provides recommendations concerning sample size, location, and duration of observations, in order to design efficient monitoring programs, based on the use of portable short period traffic counters (SPTCs), and permanent traffic counters (PTCs). The AADT on a given road section is estimated according to the following steps: 1) the count of traffic volumes of the road section in question for a short period (SPTCs in this paper); 2) identification of the

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road group to which the road section in question is similar in terms of traffic flow patterns; 3) estimation of AADT by adjusting SPTCs with an appropriate seasonal adjustment factor for road group.

TMG highlights the need for monitoring programs which explain the characteristics of truck movements, allowing better AADT estimates and more precise studies, such as pavement design, air quality calculations and crash statistics. The FHWA procedure can be applied to trucks, considering carefully the specificities of truck movements, although only limited studies have been carried out in this sense [2].

In the past, studies have noted some critical aspects of the FHWA procedure, including definition of road groups, assignment of a road section to a road group according to SPTC, and the importance of missing counts. Gecchele et al. [3] recently introduced fuzzy set theory to represent the vagueness of boundaries between individual road groups and measures of uncertainty (non-specificity and discord) to solve the difficulties of identifying the group which matches the given road section. In their paper, the approach was tested considering only passenger vehicle traffic patterns, and better AADT estimates were obtained, compared with previous methods. The present paper extends the analysis of the predictive capability of the approach, presenting the results obtained from its implementation based on traffic patterns of trucks.

Analysis was carried out with traffic data available from fifty Automatic Traffic Recorder (ATR) sites of the SITRA (TRAnsportation Information System) monitoring program, maintained by the Transportation Office of the Province of Venice, north-east Italy. The paper is organized as follows. Section 2 reviews the literature on the subject. Section 3 briefly describes the FHWA procedure, and Section 4 presents the proposed approach. Section 5 demonstrates a case study, the main results of which are described and discussed in Section 6. Concluding remarks are presented in Section 7.

2. Review of past works and issues

The FHWA procedure for estimating AADT has been extensively followed in past years, and three possible sources of error have been identified [4] when applying this procedure:

- Error due to day-to-day variations in traffic volumes;
- Error in grouping road segments and using wrong adjustment factors;
- Error in assigning the road segment where SPTC is used.

<u>Sampling error</u>: traffic volumes fluctuate constantly, and is a common problem in any problem of estimation in the transportation field.

<u>Error in grouping of road segments</u>: the TMG suggests three ways of identifying road groups based on data obtained at Automatic Traffic Recorder (ATR) sites: clustering analysis, geographical/functional classification, and "same road" application of adjustment factors. The choice of the "best" method for a particular context depends on the analyst's knowledge of the roadway network and the availability of traffic data. Drawbacks exist in each of them, although clustering analysis is probably the most commonly applied analytical approach.

FHWA suggests implementation of the least-squared minimum distance algorithm; although other methods have been studied and applied, including Regression Analysis [5], Genetic Algorithms [6], Artificial Neural Networks (ANNs) [5,7] and a large number of clustering methods. Among these, agglomerative hierarchical clustering (Ward's Minimum-Variance method [8], average linkage and centroid linkage [5]), partitioning (k-means [9]) and model-based clustering [10] have all been implemented and compared [11].

However, in some cases, results from cluster analysis were not considered reliable. In particular, it has been observed that:

- the clusters cannot be the same over the years; that is, the group to which an ATR site belongs may change in time [12,13];
- the clusters formed may not be clearly defined linguistically in terms of geographical/functional characteristics, given the purely mathematical nature of the process [1];
- it is often difficult to establish an "optimal" number of groups [1].

These criticisms highlight the difficulty of identifying the correct number and characteristics of road groups for a given road network. In practice, an ATR site may belong to more than one road group, and the groups cannot easily be defined in language, e.g., *commuter road, recreational road*.

Error in assignment of road segments: past studies [14,15] have noted that an incorrect assignment may lead to large errors in the estimated AADT. The use of weekly counts repeated at different times during the year is suggested by the TMG, to guarantee correct assignment and to minimize the risk of large errors [16,17].

In order to overcome these problems, some studies have suggested alternative approaches, including Artificial Neural Networks using SPTCs as input data [18-20] or multiple linear regression [21,22] and fuzzy decision trees [23], using socio-economic and demographic data.

Linear Discriminant Analysis [24] was recently successfully used to determine the group assignment of SPTCs (24 hours). These latest findings seem to be promising, in view of the desire for transportation agencies to reduce monitoring efforts by using short period counts instead of seasonal counts.

3. The FHWA procedure

The FHWA procedure consists of four steps, when clustering analysis is used to identify road groups.

Step 1: Group the ATR (Automatic Traffic Recorder) sites with similar temporal traffic volume variations;

Step 2: Determine the average seasonal adjustment factors for each road group;

Step 3: Assign the road section in question, monitored with a SPTC, to one of the groups defined in step 1;

Step 4: Apply the appropriate seasonal adjustment factor to the SPTC of the road group to produce the AADT estimate for the road section in question.

Given the weekly and monthly variations of traffic volumes, the seasonal adjustment factor for an ATR site k for the i-th day of the week of the j-th month is calculated by:

$$f_{ijk} = \frac{AADT_k}{ADT_{ijk}} \tag{1}$$

where $AADT_k$ is the AADT for the k-th ATR site, and ADT_{ijk} is the average daily traffic recorded on the i-th day of week of the j-th month in the k-th ATR site. The AADT and ADT are generally calculated according to the AASHTO method [25]. ATR sites are grouped by means of one of the clustering methods, according to the reciprocal of seasonal adjustment factors rf_{ijk}, defined as:

$$rf_{ijk} = \frac{1}{f_{ijk}} \tag{2}$$

Since ATR sites grouped together are presumed to have similar traffic patterns, the seasonal adjustment factors which correspond to (i,j) combinations are calculated for each road group. If n ATR sites are in road group c, the seasonal adjustment factor for the i-th day of the week of the j-th month is calculated by:

$$f_{ijc} = \frac{1}{n}\sum_{k=1}^{n}\frac{AADT_k}{ADT_{ijk}} = \frac{1}{n}\sum_{k=1}^{n} f_{ijk} \tag{3}$$

where $AADT_k$ and ADT_{ijk} for the k-th ATR site in group c are the same as in Eq. 1.

Once a road section is assigned to a group c, AADT can be estimated by multiplying daily traffic count DT_{ij} obtained for the i-th day of week of the j-th month by the corresponding seasonal adjustment factor f_{ijc}:

$$AADT_{Estimate} = DT_{ij} f_{ijc} \tag{4}$$

where *DT* is the 24-hour volume obtained from SPTC; if SPTC is for more than 24 hours, then *DT* is the average 24-hour volumes for the duration of SPTC.

4. Proposed approach

The proposed approach [3], shown in Figure 1, allows the analyst to deal with the situation when a road segment appears to belong to more than one group and to provide the degree of belonging to each group, while preserving the framework of the FHWA procedure. The approach consists of four steps:

1. Group the ATR sites using the fuzzy C-means algorithm based on the seasonal adjustment factors of individual ATR (see section 1 of Fig.1);
2. Assign the road segment for which SPTC is available to one or more predefined road groups, using neural networks (see section 2 of Fig.1);
3. Calculate the measures of uncertainty associated with the assignment to road groups (see section 3 of Fig.1);
4. Estimate AADT as the weighted average of SPTC daily volumes adjusted by seasonal adjustment factor of the assigned road group(s) (see section 4 of Fig.1).

These steps are briefly explained below; for further details, see Gecchele et al. [3].

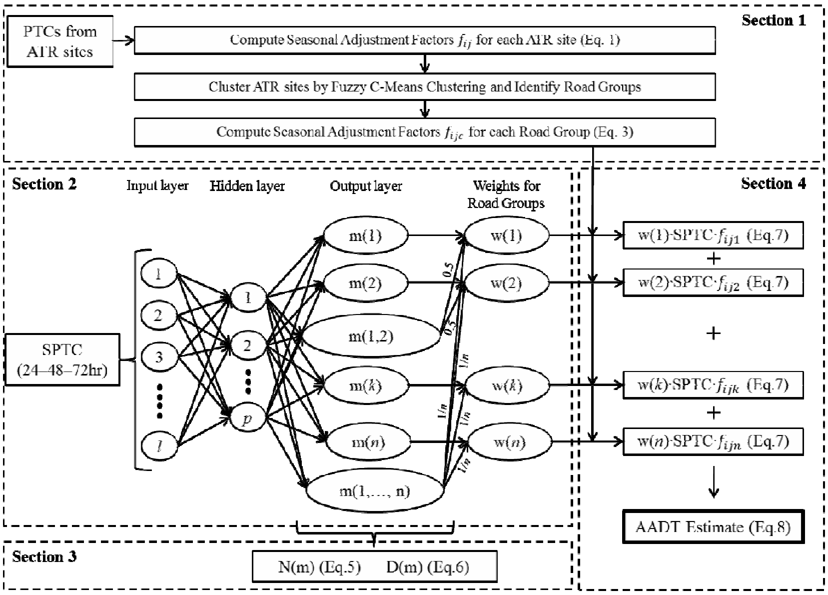

Fig. 1. Scheme of proposed approach. Source: Gecchele et al. [3]

4.1. Grouping Step

Given an ATR for site *i*, it may belong to more than one group with different degrees, between 0 and 1, where 0 indicates no belonging to a group, and 1 represents complete belonging (fuzzy boundaries). The Fuzzy C-means algorithm [26] is used to implement clustering, assuming fuzzy boundaries of groups. Given the number of groups C, the algorithm provides the degree to which an ATR site belongs to each group.

4.2. Assignment Step

In this study, a multi-layered, feed-forward, back-propagation design is used to assign the input, i.e., the given SPTC's hourly volume fluctuation (as defined in Eq. 9), to the output, represented by the road group(s) which matches the pattern.

4.3. Measures of uncertainty in assignments

The uncertainty associated with assigning a road section to road groups is investigated by means of two measures developed in the Dempster-Shafer theory [27], *Non-Specificity* and *Discord*, for which expressions are provided.

Consider that the output nodes of the neural network represent all possible combinations of road groups (*2n*), given by the power set of road groups 1 to *n* (e.g. ,(1 or 2), (1 or 2 or 3)). Consider also that the weight associated with each final node is the degree to which the traffic pattern supports individual power sets of road groups.

Let the weights associated with final node be $m(x)$, where x is a road group or more than one road group, and $\sum m(x)=1$. When $m(A)=1$, it is certain that the road section in question belongs to road group A. When $m(A \text{ or } B)=1$, the road section in question belongs either A or B, but which is uncertain. When $m(X)=1$, where X is all road groups, the road section in question may belong to any one of the group, i.e., the situation of "I don't know". Given this probability distribution, $m(x)$, the measure of non-specificity, $N(m)$, and the measure of conflict $D(m)$, are developed.

$N(m)$ provides the measure of uncertainty that the available traffic pattern fluctuation has no specific information about which road group the road section belongs to. This may be calculated by:

$$N(m)=\sum_{A\in\mathcal{F}} m(A)\cdot\log_2|A| \tag{5}$$

where $|A|$ is the number of road groups in power set A. The value of $N(m)$ is within $[0, \log_2|X|]$. X is the universal set (all road groups) and $|X|$ is the number of these groups. The minimum of $N(m)$ is obtained when $m(A)=1$, or the probability of belonging to a particular road group is one. The maximum of $N(m)$ corresponds to the case of "not able to assign to any specific group".

$D(m)$ provides the measure of uncertainty to which the available traffic pattern contains conflicting information, that is, a certain pattern at a particular time points to one group and at other times points to another group. It may be calculated by:

$$D(m)=-\sum_{A\in\mathcal{F}} m(A)\log_2\left(\sum_{B\in\mathcal{F}} m(B)\frac{|A\cap B|}{|B|}\right) \tag{6}$$

where $|B|$ and $|A\cap B|$ are the numbers of power sets associated with group B and for the intersections among subsets A and B, respectively. These measures are used to characterize the traffic pattern data collected, SPTC, at the road section which is to be classified to one or more of the predefined road groups.

4.4. Estimating AADT

The final step is estimating AADT from the available SPTC. The degree to which a road section belongs to each group, which is found by the output of the neural networks, is used to calculate AADT. For example, if the degrees of belonging to road group 1 and (1 or 2) are $m(1)$= 0.4, and $m(1,2)$=0.6, respectively, the final weights adopted for the estimation are calculated as $w(1)$= 0.4+0.6/2 = 0.7 and $w(2)$= 0.6/2= 0.3. Therefore, the AADT estimate for a given SPTC is calculated by:

$$AADT = w(1)\cdot SPTC\cdot f_{ij1} + w(2)\cdot SPTC\cdot f_{ij2} = 0.7\cdot SPTC\cdot f_{ij1} + 0.3\cdot SPTC\cdot f_{ij2} \quad (7)$$

where f_{ij1} and f_{ij2} are found in Eq. 3. In the case of 48-hour and 72-hour SPTCs, the estimation is repeated 2 or 3 times with 24-hour volume data, averaging these AADT estimates to obtain the final AADT estimate. For example, for a 72-hour SPTC (3 monitoring days), the final AADT estimate is given by Eq. 8, where $AADT_m$ is the AADT estimated according to the 24-hour volume data of the m-th monitoring day:

$$Final\ AADT = \frac{AADT_1 + AADT_2 + AADT_3}{3} \quad (8)$$

5. Case study

The proposed approach was implemented in a real-world situation, with traffic data obtained in the Province of Venice, Italy. Given the ATR sites in the road network, the Fuzzy C-means algorithm was used to establish road groups for trucks. A large number of SPTCs were extracted from each ATR site, and the AADT was estimated from each SPTC, comparing the estimates with the actual AADT of the ATR site.

5.1. Data used

The traffic data for this study were volumes obtained for the year 2005 at 50 ATR sites located on the rural roads of the Province of Venice [28]. The road network consists of two-lane roads and each ATR monitors directional traffic volumes on a single lane, describing the temporal traffic patterns in great detail [24,11]. Volume data were analysed according to a 2-class scheme, which divides passenger vehicles from truck vehicles with reference to a 5 m-length threshold. As already noted, this paper focuses on estimating AADT for truck vehicles only, because traffic patterns for trucks were found to be different from those of passenger vehicles [1].

5.2. Data treatment

The total amount of available data was 11,694 days of counts. Hourly volumes of each ATR site were sampled to form SPTCs of different durations (24-72 hours) for the road sections for which AADT was to be estimated. Analysis was carried out according to the stratified holdout approach [29]. The full dataset was divided into a calibration dataset (70% of data) and a validation dataset (30% of data), to train the ANN and to test the accuracy of the AADT estimates, respectively. This means that the latter SPTCs were used as input for the ANN which was developed from the training dataset.

5.3. Model implementation

Three tasks are conducted to implement the proposed model: establishing road groups, developing and executing the artificial neural networks, and calculating AADT.

5.3.1. Establishing road groups according to Fuzzy C-Means

Data from the 50 ATR sites were used to establish road groups. Eighteen seasonal adjustment factors were used to describe the seasonal variations of truck flow at each site, according to the combination of 3 day-types (Weekdays, Saturdays, Sundays) and 6 two-month periods (period 1 = January-February, period 2 = March-April, period 3 = May-June, period 4 = July-August, period 5 = September-October, period 6 = November-

December). This choice reflects the structure of the SITRA monitoring program currently used by the Province of Venice.

The implementation of the Fuzzy C-means algorithm means that the number of groups (C) must be specified in advance. Since the appropriate number was not known *a priori*, the algorithm was tested by changing the values of C from 2 to 20. The best number of groups was chosen by comparing the values of the Dunn Index [30], Silhouette measure [31], Pseudo F Statistic [32] and G2 index [33]. The robustness of the solution was also tested by running the algorithm for different time periods, changing the starting point, and verifying the stability of results. According to these criteria, the best number of groups was found to be 5 for this case study.

Once the number of groups was fixed at 5, the belonging of each ATR to a road group was identified by analysing the values of membership grades (see Hanesh et al. [34] and Gecchele et al. [3] for details). Four “I don’t know” cases were identified: Group “1 or 2 or 4” (3 ATRs), Group “1 or 4” (5 ATRs), Group “1, 3 or 4” (3 ATRs) and Group (1,…,5), which was the case of total ignorance, or “I don’t know at all” (2 ATRs). Figure 2 shows the average reciprocals of seasonal adjustment factors rf_{ijk} (Equation 2) for different days and periods of the year for each well-defined group. Traffic patterns for trucks were similar among groups, the weekly traffic pattern being repeated approximately in the same manner at different periods of the year.

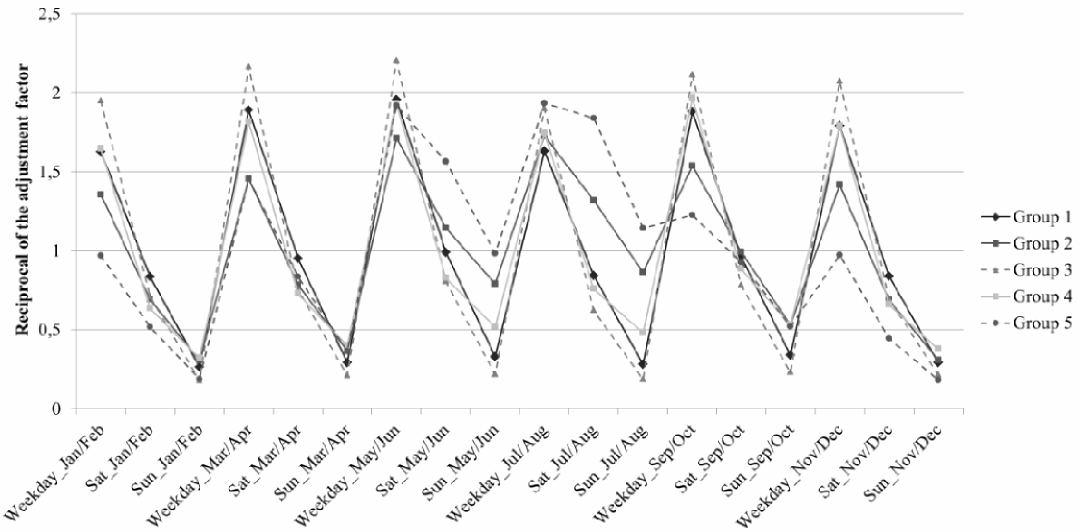

Fig. 2. Combinations of type of day and two-month period vs. average reciprocals of seasonal adjustment factors rf_{ij} for road groups.

Patterns for Group 2 (7 ATRs) and Group 5 (6 ATRs) were associated with recreational roads, since they have lower volumes in winter and higher ones during summer weekends. The other groups (Group 1 (6 ATRs), 4 (4 ATRs) and 3 (14 ATRs)) include more clear-cut commuter roads and differ mainly in the extent of the decrease in traffic volumes observed during weekends. These groups only partially match those found for passenger vehicles [3], owing to the different traffic patterns of passenger vehicles and trucks, and highlights the need and usefulness of separating analysis for different vehicle classes.

5.3.2. Developing Artificial Neural Networks

Multi-layered, feed-forward artificial neural networks (ANNs) were developed to assign the SPTCs to the road groups, adopting different structures of ANN, since the approach was tested on 24-, 48- and 72-hour SPTCs.

Some basic points are common to the three cases:

- the input layer included one node describing the two-month period of the year, one describing the type(s) of day of the SPTCs, and one for each hourly factor taken from the SPTC. The hourly factor, h_l, was defined by:

$$h_l = \frac{HT_l}{DT} \tag{9}$$

  where l= 0, …, 23 was the starting time for the hourly count, HT_l was the hourly traffic volume for hour l, and DT was the daily traffic for the specific SPTC. Therefore, 24 hourly factors were available for the 24-hour SPTCs, 48 for the 48-hour ones, and 72 for the 72-hour ones;
- the output layer had a node for each road group and nodes for all the power sets, such as Group (1 or 4), Group (1 or 2 or 4), including Group (1,…,5), which was the case of total ignorance or “I don’t know at all”;
- one hidden layer was used, with a variable number of nodes depending on the type of SPTCs adopted: 18 for the 24-hour ANNs, 30 for the 48-hour ones, and 42 for the 72-hour ones;
- the ANNs were trained with the back-propagation algorithm, and the sigmoid transfer function was used.

As regards the type of day of the SPTC, the analysis considered SPTCs taken during the 3 day-types (Weekdays, Saturdays, Sundays) separately for the 24-hour samples, counts taken during weekdays (Mondays, Tuesdays, Wednesdays, Thursdays) from counts taken on Saturdays-Sundays for the 48-hour samples, counts taken during weekdays (Mondays, Tuesdays, Wednesdays) and counts taken on Fridays-Saturdays-Sundays for the 72-hour samples.

5.3.3. Calculation of AADT

In this step, each SPTC in the test dataset was assigned by the corresponding ANN, yielding the probabilities of belonging to each road group. The SPTC volume was used to estimate the AADT according to Eq. 6 for 24-hour SPTCs and Eq. 7 for the other two.

6. Results and discussion

6.1. Examination of estimated AADT

The actual AADT for an ATR site and that estimated from each SPTC for the same site were compared. The goodness of the estimate was measured by the percent absolute estimation error:

$$\Delta = \left| \frac{AADT_{Estimate} - AADT_{Actual}}{AADT_{Actual}} \right| \times 100 \tag{10}$$

The Mean Absolute Error (MAE) and the Standard Deviation of Absolute Error (SDAE) were used to analyse the accuracy of the resulting AADT estimates. Table 1 lists some details about MAEs and SDAEs for different tests: by group, different durations of SPTCs, and different day-types (weekdays, weekends, weekdays + weekends). Table 1 lists the MAE and SDAE obtained by using only samples with low discord values (< 20% of maximum) for weekdays, together with the percentage of samples passing this threshold. Figure 3 shows the MAEs obtained for 13 ATR sites, analysing different durations and the use of SPTCs with low discord values (<

20% of maximum). For the same ATR sites Figure 4 shows the percentage of SPTCs of different durations with low non-specificity values (< 25% of maximum).

As in Gecchele et al. [3], the following observations may be made, according to the results shown in Table1:

- Recreational roads (Groups 2, 5) have large MAE and SDAE values compared with those of commuter roads (Groups 1, 3, 4), due to the higher variability in traffic patterns.
- SPTCs taken on weekdays give a more accurate AADT estimate compared with those taken during weekends; the reduction of MAE and SDAE increases when longer SPTCs are used.

Table 1. MAE and SDAE of road groups for different combinations of SPTC and time periods

SPTC [hrs]	Group	MAE [%]					SDAE [%]			
		Total	Weekdays			Weekends	Total	Weekdays		Weekends
		ANN	ANN	D <20%	Samples	ANN	ANN	ANN	D <20%	ANN
24	1	15.1	12.1	11.1	27.5%	22.6	14.8	11.3	11.8	18.9
24	2	27.7	14.8	17.8	21.1%	46.9	42.7	12.0	16.8	60.6
24	3	16.2	14.2	13.3	25.7%	21.7	14.6	12.3	13.4	19.2
24	4	15.4	11.6	13.1	58.2%	25.8	21.0	14.2	17.0	30.4
24	5	30.0	15.5	17.2	61.6%	58.5	46.6	13.0	14.1	70.2
48	1	13.8	12.2	12.2	83.5%	20.3	15.5	14.6	15.0	17.3
48	2	26.8	15.6	15.0	85.1%	52.1	36.3	11.0	10.8	55.8
48	3	14.3	13.6	12.5	84.2%	17.7	13.2	13.1	12.8	13.2
48	4	11.6	10.1	9.7	88.3%	17.9	13.2	9.4	9.1	22.0
48	5	23.7	12.1	12.1	83.3%	59.9	41.0	9.7	9.7	70.0
72	1	9.5	9.8	8.8	82.5%	8.3	10.3	10.9	9.9	7.6
72	2	21.1	15.6	15.6	79.8%	30.6	18.9	10.0	10.0	25.6
72	3	11.8	12.2	11.6	93.6%	10.8	12.1	12.7	12.4	9.7
72	4	9.5	9.2	9.2	98.3%	10.7	7.5	7.0	7.0	9.0
72	5	24.4	11.5	11.5	85.1%	54.1	34.6	9.9	9.7	49.6

NOTES: ANN = assignment with proposed model, D < 20% = assignment with proposed model using SPTCs with discord < 20% of maximum, Samples = percentage of samples with discord D < 20% of maximum, Total = Weekdays + Weekends STPCs.

The uncertainty measures also provide information on the quality of AADT estimates and improve their interpretability:

- Using SPTCs with low values of discord (< 20% of maximum) generally provides more accurate AADT estimates than all SPTCs. However, as Figure 3 shows, the difficulty in classifying particular road groups and the reduction in AADT estimation errors differ among ATR sites;

- Using the non-specificity measure highlights those SPTCs which are difficult to assign to a specific road group. Figure 4 shows that ATR sites 7, 8 and 9 have low percentages of samples with low values of non-specificity, unlike other sites with high percentages of samples (e.g., ATR sites 1 to 6). The former sites are classified as “I don’t know” cases, whereas the latter clearly belong to a group. Note also that an increase in the duration of counts increases the number of SPTCs with low values of non-specificity, mainly for sections clearly belonging to a group and not for “I don’t know” ones.

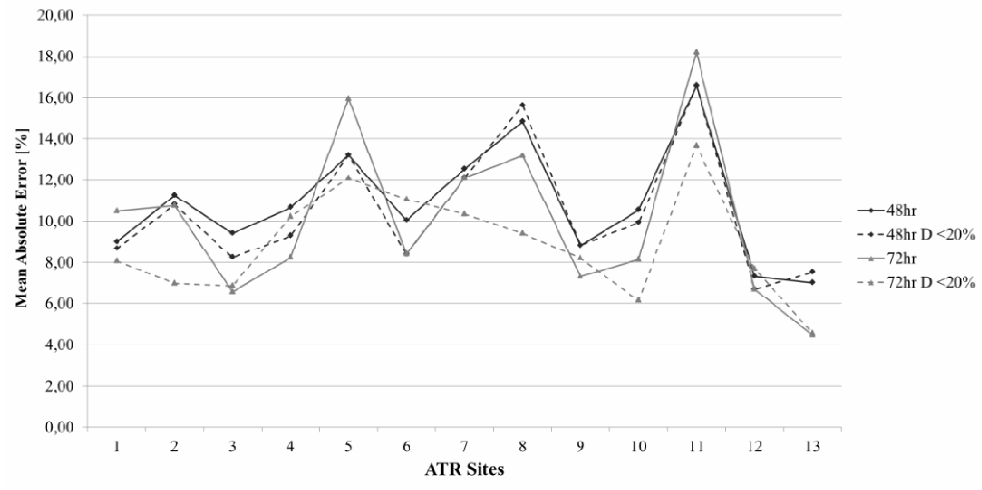

Fig. 3. Mean Absolute Error [%] for 13 ATR sites, according to different SPTC durations

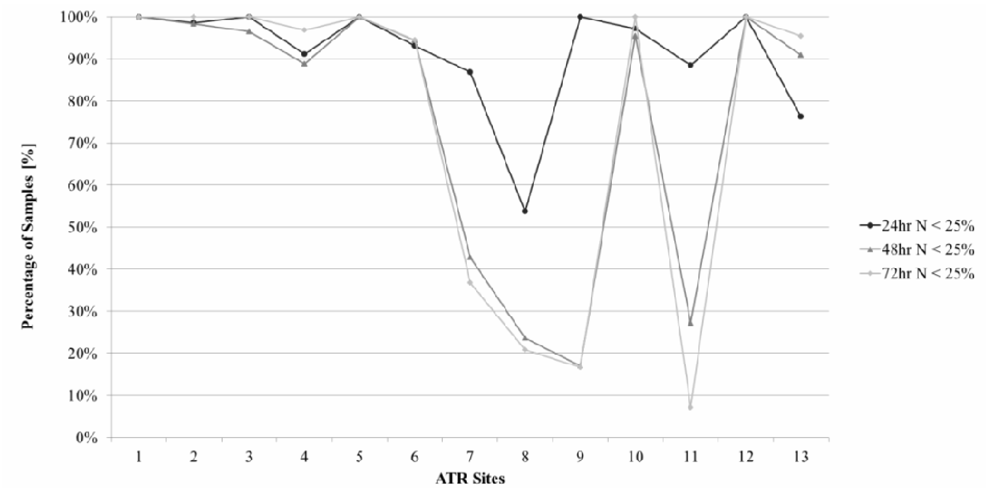

Fig. 4. Percentage of samples with Non-specificity< 25 % of maximum for 13 ATR sites

6.2. Comparison with another model

The AADTs estimated with the proposed approach were also compared with those obtained by another approach proposed in previous studies, with 72-hour SPTC data taken on weekdays. The model proposed by Sharma et al. [18] is an ANN with hourly factors as inputs and AADT estimates as output, which does not require the definition of road groups. The resulting MAEs are listed in Table 2, according to the road groups from which the SPTCs were extracted, and compared with the proposed approach.

Table 2 shows that the AADTs estimated by the proposed approach give a lower MAE compared with Sharma et al. The differences are significant (Paired t-test at a 95% confidence level) for all groups, except group 4, and much larger than the differences observed for passenger vehicles [3].

Table 2. Comparison of MAE [%] of proposed model with Sharma et al. [18] with 72-hour SPTCs taken on weekdays

SPTC [hrs]	Group	ANN	Sharma et al.
72	1	9.8	53.6
72	2	15.6	95.7
72	3	12.2	33.1
72	4	9.2	10.8
72	5	11.5	115.1

7. Summary and conclusions

In this work a new approach based on limited traffic counts has been applied to estimate the ADDT for truck vehicles. This approach, based on the structure of the FHWA method, introduces mechanisms to deal with the vagueness of boundaries between individual road groups and adopts measures of uncertainty (non-specificity and discord) to solve the difficulties of identifying the group which matches the given road section.

Truck traffic data from 50 ATR sites in the road network of the Province of Venice, Italy, were adopted for this analysis. The results were similar to those obtained for passenger vehicles:

- the accuracy of AADT estimates, measured by MAE and SDAE, was found to be satisfactory;
- SPTCs, preferably lasting 72 hours, should be used during weekdays, for the most accurate AADT estimates. This result is interesting, as weekdays are more important than weekends for truck traffic analysis;
- an increase in SPTC duration results in a decrease in errors in AADT estimates;
- discord and non-specificity are useful measures to evaluate the quality of estimates, suggesting the need for additional data collection. A low value of discord indicates more accurate AADT estimates, and a high value of non-specificity indicates uncertain assignment of SPTCs to road group(s).

In the future, this work should be extended, in view of the influence of the socio-economic and land-use characteristics of the environment of the road section when road groups are identified and SPTCs assigned.

References

[1] FHWA. (2001). *Traffic Monitoring Guide*. U.S. Department of Transportation.

[2] Hallenbeck, M., Rice, M., Smith, B., Cornell-Martinze, C., & Wilkinson, J. (1997). *Vehicle Volume Distribution by Classification*. FHWA.

[3] Gecchele, G., Rossi, R., Gastaldi, M., & Kikuchi, S. (2012). Advances in Uncertainty Treatment in the FHWA Procedure for Estimating Annual Average Daily Traffic Volume. *TRB Transportation Research Board 91st Annual Meeting*. Washington, D.C.

[4] Bodle, R. (1967). Evaluation of Rural Coverage Count Duration for Estimating Annual Average Daily Traffic. *Highway Research Record, 199*, 67-77.
[5] Faghri, A., & Hua, J. (1995). Roadway Seasonal Classification Using Neural Networks. *Journal of Computing in Civil Engineering, 9*(3), 209-215.
[6] Lingras, P. (2001). Statistical and Genetic Algorithms Classification of Highways. *Journal of Transportation Engineering, 127*(3), 237-243.
[7] Lingras, P. (1995). Hierarchical Grouping Versus Kohonen Neural Networks. *Journal of Transportation Engineering, 121*(4), 364-368.
[8] Sharma, S. C., & Werner, A. (1981). Improved Method of Grouping Provincewide Permanent Traffic Counters. *Transportation Research Record, 815*, 12-18.
[9] Flaherty, J. (1993). Cluster Analysis of Arizona Automatic Traffic Record Data. *Transportation Research Record, 1410*, 93-99.
[10] Zhao, F., Li, M.-Y., & Chow, L. (2004). *Alternatives for Estimating Seasonal factors on Rural and Urban Roads in Florida*. Research Office. Florida Department of Transportation.
[11] Gecchele, G., Caprini, A., Gastaldi, M., & Rossi, R. (2011). Data mining methods for traffic monitoring data analysis. A case study. *Procedia Social and Behavioral Sciences, 20*, 455-464.
[12] Ritchie, S. (1986). A Statistical Approach to Statewide Traffic Counting. *Transportation Research Record, 1090*, 14-21.
[13] Faghri, A., Glaubitz, M., & Parameswaran, J. (1996). Development of Integrated Traffic Monitoring System for Delaware. *Transportation Research Record, 1536*, 40-44.
[14] Gulati, B. (1995). *Precision of AADT Estimates from Short Period Traffic Counts*. M.S. thesis, University of Regina. Saskatchewan, Canada.
[15] Davis, G. (1996). *Estimation Theory Approaches to Monitoring and Updating Average Daily Traffic*. University of Minnesota, Center of Transportation Studies, Minneapolis, USA.
[16] Davis, G., & Guan, Y. (1996). Bayesian Assignment of Coverage Count Locations to Factor Groups and Estimation of Mean Daily Traffic. *Transportation Research Record, 1542*, 30-37.
[17] Davis, G. (1997). Accuracy of Estimates of Mean Daily Traffic: A Review. *Transportation Research Record, 1593*, 12-16.
[18] Sharma, S., Lingras, P., Xu, F., & Liu, G. (1999). Neural Networks as Alternative to Traditional Factor Approach to Annual Average Daily Traffic Estimation from Traffic Counts. *Transportation Research Record, 1660*, 24-31.
[19] Sharma, S., Lingras, P., Liu, G., & Xu, F. (2000). Estimation of Annual Average Daily Traffic on Low-Volume Roads. Factor Approach Versus Neural Networks. *Transportation Research Record, 1719*, 103-111.
[20] Sharma, S., Lingras, P., Xu, F., & Kilburn, P. (2001). Application of Neural Networks to Estimate AADT on Low-Volume Roads. *Journal of Transportation Engineering, 127*(5), 426-432.
[21] Seaver, W., Chatterjee, A., & Seaver, M. (2000). Estimation of Traffic Volume on Rural Local Roads. *Transportation Research Record, 1719*, 121-128.
[22] Li, M.-T., Zhao, F., & Wu, Y. (2004). Application of Regression Analysis for Identifying Factors That Affect Seasonal Traffic Fluctuations in Southeast Florida. *Transportation Research Record, 1870*, 153-161.
[23] Li, M.-T., Zhao, F., & Chow, L. (2006). Assignment of Seasonal Factor Categories to Urban Coverage Count Stations Using a Fuzzy Decision Tree. *Journal of Transportation Engineering, 132*(8), 654-662.
[24] Tsapakis, I., Schneider, W., Bolbol, A., & Skarlatidou, A. (2011). Discriminant Analysis for Assigning Short-Term Counts to Seasonal Adjustment Factor Groupings. *Transportation Research Record, 2256*, 112-119.
[25] AASHTO. (1992). *AASHTO Guidelines for Traffic Data Programs*. Joint Task Force on Traffic Monitoring Standards, AASHTO, Washington, D.C.
[26] Bezdek, C., Ehrlich, R., & Full, W. (1984). FCM: the Fuzzy c-Means Clustering Algorithm. *Computational Geosciences, 10*, 191-203.
[27] Klir, G., & Wierman, M. (1999). *Uncertainty-Based Information. Elements of Generalized Information Theory* (Second ed.). Heidelberg, Germany: Physica-Verlag.
[28] Della Lucia, L. (2000). *Campagna di monitoraggio del traffico sulla rete di interesse regionale 1999-2000*. Dip. Costruzioni e Trasporti, Regione Veneto, Province del Veneto, Padova.
[29] Witten, I., & Frank, E. (2005). *Data Mining: Practical Machine Learning Tools and Techniques* (Second ed.). San Francisco: Morgan Kaufmann.
[30] Dunn, J. (1974). Well Separated Clusters and Optimal Fuzzy Partitions. *Journal of Cybernetics, 4*(1), 95-104.
[31] Rousseeuw, P. (1987). Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics, 20*, 53-65.
[32] Calinski, R., & Harabasz, J. (1974). A Dendrite Method for Cluster Analysis. *Communications in Statistic, 3*, 1-27.
[33] Goodman, L., & Kruskal, W. (1954). Measures of Association for Cross-validation. *Journal of the American Statistical Association, 49*, 732-764.
[34] Hanesh, M., Sholger, R., & Dekkers, M. (2001). The Application of Fuzzy C-Means Cluster Analysis and Non-Linear Mapping to a Soil Data Set for the Detection of Polluted Sites. *Physics and Chemistry of the Earth, 26*(11-12), 885-891.